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New approaches to evacuation modelling for fire safety engineering applications

Enrico Ronchi[1], Alessandro Corbetta[2], Edwin. R. Galea[3], Max Kinateder[4], Erica Kuligowski[5], Denise McGrath[6], Adam Pel[7], Youssef Shiban[8], Peter Thompson[9] & Federico Toschi[10]

[1] Division of Fire Safety Engineering, Lund University, Sweden
[2] Department of Applied Physics, Eindhoven University of Technology, The Netherlands
[3] Fire Safety Engineering Group, University of Greenwich, UK
[4] NRC Construction – Fire Safety, National Research Council, Canada
[5] Fire Research Division, National Institute of Standards and Technology, USA
[6] School of Public Health, Physiotherapy and Sports Science, University College Dublin, Ireland
[7] Transport and Planning, Delft University of Technology, The Netherlands
[8] Department of Psychology, PFH Private University Göttingen, Germany
[9] Generative Design division, Autodesk Inc., USA
[10] Department of Applied Physics and department of Mathematics and Computer Science, Eindhoven University of Technology, The Netherlands

Abstract. This paper presents the findings of the workshop "New approaches to evacuation modelling", which took place on the 11th of June 2017 in Lund (Sweden) within the Symposium of the International Association for Fire Safety Science (IAFSS). The workshop gathered international experts in the field of fire evacuation modelling from 19 different countries and was designed to build a dialogue between the fire evacuation modelling world and experts in areas outside of fire safety engineering. The contribution to fire evacuation modelling of five topics within research disciplines outside fire safety engineering (FSE) have been discussed during the workshop, namely 1) Psychology/Human Factors, 2) Sociology, 3) Applied Mathematics, 4) Transportation, 5) Dynamic Simulation and Biomechanics. The benefits of exchanging information between these two groups are here highlighted in light of the topic areas discussed and the feedback received by the evacuation modelling community during the workshop. This included the feasibility of development/application of modelling methods based on fields other than FSE as well as a discussion on their implementation strengths and limitations. Each subject area is here briefly presented and its links to fire evacuation modelling are discussed. The feedback received during the workshop is discussed through a set of insights which might be useful for the future developments of evacuation models for fire safety engineering.

Keywords. Evacuation modelling, Egress, Fire Safety, Human Behaviour, Emergency, Pedestrian Dynamics, Smoke, Exit choice, Pre-evacuation.

Highlights:

- Findings of a workshop on new approaches to evacuation modelling are presented.
- Five areas useful for evacuation modelling development are introduced.
- Feedback on the modelling ideas is reported
- A roadmap for implementation of new approaches is drafted

1. Introduction

The developments of evacuation models for fire safety engineering applications have reached a crossroads. An extensive list of sub-models are today available for the representation of the behavioural and physical components of evacuation (e.g., pedestrian movement, evacuation decisions, route choice, social influence, etc.) (Ronchi and Nilsson, 2016). Model developers face the choice of tuning parameters and variables of existing sub-models or to begin incorporating new features based on insights from outside the field of fire safety engineering.

Evacuation modelling for fire safety engineering applications is a multi-disciplinary research area *per se* since it combines both behavioural sciences (e.g. psychology, sociology, etc.) for the representation of human behaviour in fire as well as engineering and natural sciences (e.g. computer science, physics, physiology, applied mathematics, etc.) for the development and implementation of the models into simulation tools. Those tools are generally used in fire safety engineering for the design of buildings and transportation systems within the performance-based design approach (Meacham, 1997).

To date, scientists from fields outside of fire safety engineering have investigated behavioural and physical issues associated with human behaviour in fire, crowd dynamics and pedestrian monitoring which may potentially be relevant to evacuation modelling. The critical question is if/how such insights can be integrated into the existing body of fire evacuation models. Based on this starting point, a set of challenges need to be analysed concerning the possible uses and suitability of such studies in the field of evacuation modelling for fire safety engineering applications. These challenges include, identifying relevance (Is the research relevant to human behaviour in fire?), maturity (How well established are findings within their discipline?), and applicability (How can we implement basic research findings into an evacuation model?) of research, but also finding a common vocabulary and overcoming jargon from within each discipline. In short, models, methods, data, and theories from other fields need to be assessed for their suitability for evacuation models. This process should run in parallel with identifying and filling potential knowledge gaps in existing evacuation models (Galea, 2012).

To facilitate this process, the workshop "*New approaches to evacuation modelling*" was held as part of the Symposium of the International Association for Fire Safety Science (IAFSS) hosted by Lund University in Lund (Sweden) on the 11th of June 2017. The workshop brought together a set of international experts from various disciplines outside of fire safety engineering with invited evacuation modelling experts in order to discuss new ideas for future evacuation modelling developments. Researchers, evacuation model developers, users and experts as well as fire safety practitioners and regulators took part in the workshop. Participants came from 19 different countries, reflecting the global relevance of the topic. Another key motivation of the workshop was to stimulate collaborations between specialists of different disciplines and increase the visibility of fire safety engineers in areas outside of their "usual" boundaries.

A set of disciplines were selected during the preparation of the workshop and relevant experts from each discipline were invited to form a panel and present an overview of each subject and discuss possible issues which might be relevant to evacuation modelling for fire safety engineering applications with the workshop audience. The reasons behind the selection made by the workshop organizers on the set of disciplines discussed were mostly linked to 1) potential of the area findings to be implemented in existing evacuation modelling tools, 2) estimated time for implementation of area findings (e.g., in a relatively short time, thus excluding fields which are at a relatively early stage of research, and 3) interest/availability of researchers working in an area different than fire safety engineering to contribute to the workshop 4) time available within the workshop to discuss the selected topics. In fact, in order to achieve a constructive dialogue during the workshop, it was necessary to identify an area expert willing to present the topic and engage in the discussion with the fire safety engineering community. Furthermore, only a limited number of topics could be addressed within the time available. The audience consisted of a heterogeneous group of parties interested in evacuation modelling, including researchers, regulators (e.g. authorities having jurisdictions and fire code developers), practitioners, and students. Nevertheless, the majority of the audience were researchers and/or students and so the support for the suggested needs and proposed developments presented are primarily driven by a researcher perception rather than an end-user perception.

Here, the main conclusions of the workshop as well as the five presentations and their accompanying discussion are summarized. In addition, a roadmap for the integration of the advances in interdisciplinary research into fire evacuation models is proposed. The final part of this paper discusses the steps and actions that could be taken to improve current evacuation modelling tools for fire safety engineering applications. More information about the workshop, along with the full articles associated with each presentation can be found in a Lund University report associated with the workshop (Ronchi et al., 2017).

2. Workshop structure

Five experts (the acronyms here refer to the initials of each paper author) from psychology/human Factors (MK, YS), sociology (EK), applied mathematics (AC, FT), transportation research (AP), and dynamic simulation/biomechanics (PT, DM) presented their work. Each presentation was followed by a questions & answers (Q&A) session with the workshop panel moderated by two experts from the evacuation modelling community (ER, EG). The Q&A session gave the opportunity to the audience to comment on potential issues associated with the implementation of the proposed methods/theories/data/ideas and discuss strategies for improvement of current evacuation models based. The workshop closed with an open discussion in which the workshop participants had the opportunity to present comments, questions and remarks directly to the presenters of each disciplines and/or other experts from the evacuation modelling community.

The next sections present an overview of the five disciplines presented during the workshop, namely 1) psychology/human factors, 2) sociology, 3) applied mathematics, 4) transportation, 5) dynamic simulation and biomechanics. The disciplines were selected after a review made by the workshop organizers of the scientific outputs in different subject areas which may be potentially integrated into evacuation modelling tools for fire safety engineering applications[1]. Each presenter focussed on a sub-set of key subject areas within each discipline which could be relevant for future evacuation model developments.

The selected subject areas presented were:

1) Psychology/Human factors: Visual Perception, Social Influence, and Emotional States

[1] The organizers had to limit themselves to a select number of fields which were deemed most relevant and in which some previous work directly applicable to evacuation modeling had been published. Note, however, that many other disciplines could provide potential insights on human behavior in fire, for example physiology/kinesiology, artificial intelligence/machine learning, data scientists/big data, or geography, just to name a few.

2) Sociology: A Multi-disciplinary Perspective on Representing Human Behaviour in Evacuation Models
3) Applied Mathematics: Overhead pedestrian tracking for large scale real-life crowd dynamics analyses
4) Transportation: Evacuation Modelling in the field of Transport
5) Dynamic simulation and biomechanics: An analysis of human biomechanics and motor control during evacuation movement.

3. Psychology/Human Factors: Visual Perception, Social Influence, and Emotional States

The uses and effectiveness of evacuation models relies on understanding human perception and action in emergency situations. Recent developments pushed the possibilities as to what aspects of human behaviour in fire can be modelled (Kinateder et al., 2014d; Kuligowski et al., 2017). However, there seems to be a gap between basic research and model development. This might be attributed to the difficulty in translating findings from a basic laboratory experiment into valid predictions on how people would react in a wide range of emergency situations.

Aspects that influence *individual* occupant evacuation behaviour were discussed and an attempt to connect the existing approaches in evacuation modelling was made. The key question of this presentation were: What information is available to an evacuee at what time? How is this information processed? And how does it affect behaviour? The presenter touched on three exemplary aspects that are representative for these questions. First, *perception*, i.e. the process of picking up the information that allows an organism to successfully act in its ecological niche. There are many aspects of perceptual research that are relevant to fire evacuation (e.g., vision, auditory perception, olfaction); the focus here was on visual motion perception. The second aspect was *social influence* with a focus on low density scenarios (i.e., scenarios in which behaviour is not completely restrained by physical forces). In the third section, the influence of intense emotions such as fear on spatial behaviour is discussed, linking observation that evacuees “don’t panic” (Fahy et al., 2012) to findings that show how stress and fear bias decision-making.

The three examples illustrate how basic research on human behaviour can inform evacuation model development. Perceptual processes could be simulated to inform agents about the environment. This would have the benefit that agents could navigate novel spaces with incomplete knowledge of the environment. Perceptual processes can be implemented with varying granularity: for example, modellers could specify agents’ visual field, how agents respond to dynamic changes in the environment and visibility), or even complex interactions between biomechanical constraints, eye-movement, environment and behaviour. An even more complex approach would be to model a wide range of perceptual abilities depending on the agent profile expected in a given situation (e.g. age or physical ability). Social influence and fear could be implemented as a source of biases or variance that change the probability distributions of certain behaviours (e.g., the probability to select one egress route over another) in one way or the other.

There are obvious limitations to the approach discussed here. For instance, most basic research results have been studied in controlled and isolated settings. Although the strength of the experimental method is its ability to identify causal relationships between variables, it is challenging to transform findings from lab studies into predictions about human behaviour in fire without further validating studies. However, evacuation models can only be improved if the underlying psychological and physiological processes are sufficiently understood. Evacuation models that conceptually simulate occupants as agents embedded in a sociotechnical system can benefit from a deeper understanding of the psychological, social and physical environment. Results from basic research provides surprisingly precise descriptions about how humans could potentially react in fire emergencies.

3.1. Visual perception in fire emergencies

Evacuation models often base agent behaviour on what agents "see" in a given emergency situation. In some models agents can map the environment with a so called "god view", i.e., a complete knowledge of the layout of the building in which they are (Ronchi and Nilsson, 2016). However, this might not accurately represent information uptake and wayfinding during evacuation. Other models attempt to address this issue by acknowledging that in many scenarios, agents may only have knowledge of one exit route i.e. the way they entered. However, in these cases agents are also provided with an ability to discover previously unknown exit routes through the visual detection of, and use of, emergency exit signage (Filippids et al 2008, Xie et al 2012). The process of human navigation based on visual information is referred to as visually guided locomotion and has been studied extensively (Gibson, 2014; Warren, 2006; Warren Jr et al., 2001) and applied to pedestrian behaviour in crowds (Warren, 2018) . Vision is a crucial process of information uptake during human locomotion, and, for example, gaze behaviour (i.e., where a person looks) while walking over complex terrain is immediately connected to gait behaviour and foot placement (Matthis and Fajen, 2014; Matthis et al., 2018) Most evacuation models sufficiently simplify visual perception and thus risk misrepresenting how building occupants might react to an approaching fire. For example, many evacuation models completely ignore dynamic visual features such as smoke or use the physical extinction coefficient (complex refractive index) to describe how far people can see through smoke (Ronchi et al., 2013). The example of smoke perception is used here to illustrate how perceptual processes could be better conceptualized in evacuation modelling.

One source of motion information during fire evacuation might come from smoke and flames, but what are the visual features of moving smoke? Approaching smoke is a visually rich stimulus that provides the observer with a range of potential motion cues and can be classified as fluid non-rigid motion (Aggarwal et al., 1997). As an object moves through an observers visual field, it creates characteristic patterns of motion vectors, often referred to as optic flow (Gibson, 2014) that are accessible to the visual system. Several flow-based motion cues are available to the observer, allowing to extract simple (e.g., speed and angle of moving contrast gradients) to complex (e.g., looming of a smoke plume) motion patterns. Unlike rigid objects, smoke continuously changes its shape and contrast. This creates perceptual uncertainty, which in turn might lead to bias in how humans speed and orientation of moving smoke. Studies on motion perception in fog show that reducing contrast uniformly in the visual field reduces perceived speed (Snowden and Hammett, 1998). If, however, contrast is reduced non-uniformly (decreased contrast with larger distance), speed is overestimated, indicating that the spatial distribution of contrast affect how speed is being perceived (Pretto et al., 2012). Like contrast, motion coherence can bias perceived speed of a moving stimulus. In one study, peripheral background noise (i.e. dots moving incoherently) to a central coherently moving set of dots biased participants to overestimate the stimulus speed as a function of noise level (Chuang et al., 2016). Next to basic motion cues, the visual system is able to identify more complex visual motion patterns such as optical expansion (flow based) and the change in size (not flow based) to specify approaching movement (Schrater et al., 2001).

Another question is how smoke impairs vision during navigation. Some research indicates that artificially impaired vision reduces navigation, way-finding abilities and spatial learning (Gauthier et al., 2008) as well as walking speed (Fridolf et al., 2014). That is, occupants' ability to detect exit signs and navigate egress routes depend not only on their knowledge of the spatial layout but also on the visual information available in a given moment.

Although the current example uses perception of moving smoke and may appear overly specific, it illustrates how visual information could guide agent behaviour. Many aspects of the visual environment are known to the model developer given the information available to him/her from other sources or models (e.g., the layout of the environment or the distribution and movement of smoke from a fire model). Consequently, agent behaviour could be modelled based on the rules by which physical features in the environment are translated into visual perception.

3.2. Social influence in low density crowd situations

Factors influencing agent decision-making and behaviour in low density situations are not well understood as in ambiguous emergency situations, occupants seek information and the behaviour of other occupants may be considered as a useful source of information (Kinateder, 2013). There is evidence in the literature that during dangerous situations people influence each other with regard to where to and how they navigate e.g., (Kinateder et al., 2014a, 2014b; Nilsson, 2009). As this might be the case for all occupants in the situation, behavioural uncertainty may lead to different (e.g. inadequate, delayed or better) evacuation decisions (Darley and Latane, 1968; Kinateder and Warren, 2016). Social influence can potentially affect pre-evacuation time (time from a first alarm cue onset to evacuation behaviour) and exit choice (choice of evacuation destination) (Kinateder et al., 2018; McConnell et al., 2010) and it has been object of several studies in recent years (Kinateder et al., 2014b; Köster et al., 2011; Lovreglio et al., 2016; Riad et al., 1999).

3.3. Defensive behaviour and evacuation: the role of stress and fear

Fire evacuation models attempt to describe how humans react in life threatening situations. Surprisingly, the influence of emotional responses such as fear or stress that occupants may experience during evacuation only plays a minor role in evacuation modelling. Emotions are directly linked to defensive behaviours and cause qualitative shifts decision making and behaviour to increase (or decrease) the chance of survival. Established behavioural models identified a cascade of defensive behaviour in three stages of how an organism's autonomic responses, protective reflexes, and brain responses change systematically depending on threat proximity (Löw et al., 2015).

The defense-cascade model describes three distinct stages of defensive behaviour (Fanselow, 1994). In the *pre-encounter stage*, no threat has been detected yet but a threat has been previously experienced in similar situations leading to increased vigilance. Conceptually, hearing a fire alarm could be classified into this stage, as most people have experienced fire alarms before, however mostly in non-threatening drill situations. Individuals who experienced a severe fire emergency in the past might be more vigilant when they hear a fire alarm and prepare to engage in avoidance behaviour. As soon as a threat has been detected, the organism moves on to the *post-encounter defense stage*, in which attention is focussed on threat cues, and physiological and behavioural defensive responses are generated (Campbell et al., 1997; Fanselow, 1994; Lang et al., 2000; Maren, 2001; Morgan and Carrive, 2001). Threat cues in fire emergencies could be perceiving fire cues (flames, smoke) or observing fearful behaviour in other occupants. Finally, in the *circa-strike stage* the threat is most imminent and the organism engages in active behavioural strategies accompanied with increased physiological activation (Kim et al., 2013; LeDoux, 2012). In the case of a fire evacuation, this would be an extreme situation in which threat of fire is imminent and occupants are exposed to smoke and flames or other threats. In this case, most occupants are more susceptible to fear related biases in decision-making. Each of the three stages may appear during a fire evacuation and depending on the scenario, different fear reactions can be hypothesized. Although there is a lack of empirical evidence it is possible that in most evacuation scenarios, occupants will find themselves in the pre-encounter or post-encounter defense stage, as the most common evacuation triggers are fire alarms or initial fire cues (Xiong et al., 2017).

Fear directly influences cognitive processes (e.g., attention) relevant for evacuation behaviour. Thus, basic research on fear processes may help to understand the role of fear in evacuation. For instance, cognitive biases are well documented in fearful situations and are consistently found in highly fearful participants and in patients suffering from specific phobias such as pathological fear of heights. Several studies have shown that fear influences *attention* (e.g. by narrowing it) towards threatening objects (Cisler et al., 2007; Mogg and Bradley, 2006; Öhman et al., 2001; Watts et al., 1986), and that when experiencing strong fear, attention is quickly engaged with the fearful object (Mogg and Bradley, 2006) and slow to disengage (Fox et al., 2001, 2002). Furthermore, fear inducing cues are hard to ignore and can distract from the task at hand (Gerdes et al., 2008; Okon-Singer et al., 2010). Although, not often documented in real cases, in an evacuation scenario this could explain why fearful occupants might be more susceptible to "ignore" exit signage when confronted with more salient fire cues.

Furthermore, fear might shape spatial navigation. In fearful behaviour, often manifested as avoidance in humans, a fearful person tries to increase the distance between feared stimulus or situation. Interestingly, research on rodent behaviour has shown that fearful rats exploring a square field tend to avoid open spaces and stick closer to walls compared to non-fearful rodents (Simon et al., 1994). At least one study observed similar effects in human exploration behaviour (Walz, 2013).

Importantly, the fact that fear and stress can bias evacuation behaviour is not in contrast to the fact that so called "panic" rarely occurs during evacuation (Fahy et al., 2012). Humans are able to engage in pro-social behaviour and make rational decisions when they experience fear; however, emotional states can introduce systematic biases in decision-making and spatial behaviour (Kinsey et al., 2018). Understanding, if and how much fear is typically caused by various aspects of fire evacuation scenarios, and how that fear is linked to evacuation behaviour is still unclear and it can be subject to future research but bears the potential to explain certain behavioural phenomena observed in evacuation.

4. Sociology: a multi-disciplinary perspective on representing human behaviour in evacuation models

Behavioural researchers in fire are still fighting the long-standing belief that human behaviour during fires is just too complicated to predict. At present, evacuation models focus much more on simulating, verifying, and validating the ***movement of people*** through the entire building. More specifically on the importance of tracking individuals or crowds, their physical movements, and their evacuation timing in the event of a building fire (Gwynne et al., 1999;

Kuligowski, 2016). While these tools and their underlying calculation techniques are crucial to the engineering community and performance-based analyses, many are missing a key component of building evacuation: the behavioural component. Because the movement and behavioural components are highly coupled, an evacuation modelling tool is incomplete without proper representation of both components.

The benefits and necessity of a comprehensive, conceptual model of human behaviour in fire (HBiF) for incorporation into evacuation models were discussed. Many of the current evacuation modelling tools available today rely on the user to supply a significant amount of information on behavioural representation. This information is required before a simulation is run. Current models include different behavioural aspects such delay times or behavioural itineraries. While existing behavioural approaches are a positive step toward the representation of human response within a simulation tool, the problem is that they rely primarily on the user to determine the population's behaviours before the simulation even begins (i.e., representation rather than prediction). This places a large burden on the model user; requiring a significant amount of knowledge about evacuation behaviour and theory, and based on that knowledge, the pre-determination of behaviours that are likely to emerge during the simulation.

Another method of behavioural representation is through the inclusion of component theories, either as defaults in the modelling tool, embedded input options available for users, or user configuration of the model set-up. In this context, "component theories" are behavioural findings from journal articles, authoritative reports, observations, and/or studies on human behaviour in fire and other emergencies. Each component theory focusses on a particular aspect of the fire emergency and results in one type of behavioural outcome. Component theories are often incorporated within modelling tools as behavioural rules that link one condition to one outcome (e.g., if X, then Y occurs).

The benefits of a behavioural approach using component theories is that it begins to reduce the burden on the user; and instead, involves agency at a more refined level moving us closer to producing genuinely new and unexpected results through the generation of emergent outcomes. Emergent outcomes are those that arise from the model's simulation of the evacuation scenarios, rather than outcomes pre-determined completely by the user. It is important to note that genuinely emergent outcomes can only truly occur at a less refined (higher) level than the pre-determined user intervention – and typically involves interaction between simulated agents / objects. For instance, if the user determines that an agent will definitely use a particular route, then the agent's use of the route is not emergent – no new outcome is generated. The outcome is effectively an attribute of the agent. However, the outcomes produced by the simulated population's use of that route will be emergent (e.g. the length of the queue formed); i.e. outcomes that are not an attribute of the agent. If the agent's route selection is reliant on external conditions (e.g. interaction with other agents, provision of new information, interaction with smoke, etc.), then the agent's action selection is emergent, along with all of the population-level outcomes identified above (e.g. the number of agents using the route, the congestion formed, etc.).

However, there is a problem with the behavioural approach using component theories. Typically, only a small subset of these component theories is incorporated in any one modelling tool, resulting in a piecemeal representation of HBiF. Piecemeal representations can result in inaccurate modelling results, quite possibly underestimating/overestimating evacuation timing. Instead, it is desirable is to create and incorporate a more comprehensive and inclusive representation of HBiF within evacuation modelling tools.

4.1. Improvements to Evacuation Modelling – Conceptual Modelling

With current evacuation modelling tools, the user is required to set up the initial conditions and the evacuee response (either via user-defined inputs or the selection of component theories). A new conceptual model is envisioned and it should require user-input of *only* the initial conditions, which is often times difficult enough. During simulation, these inputs would be used by the conceptual model of HBiF, to predict internal motivations of agents (i.e., risk perception), and in turn, agents' actions and associated delays.

The benefits of such a model is that it could predict, rather than simply determine based upon user input, human behaviour during fire events. This outcome alone would enable a user to identify the behaviours that emerge as the fire scenario unfolds, removing significant burden from the model user and increasing the accuracy of model results. This sub-model, after extensive validation, could be incorporated into current and future evacuation modelling tools.

Examples of existing conceptual models of human behaviour in fire relevant to the goal of predicting decisions and actions taken in a fire emergency are 1) the general model of human behaviour in fires developed by (Canter et al., 1980), 2) a conceptual model developed by Kuligowski (Kuligowski, 2011) that focusses only on pre-evacuation behaviour from a single fire event - the 2001 World Trade Center Disaster and 3) a conceptual model developed by compiling a series of component theories from various disciplines into a cohesive platform to predict whether an agent takes protection (or not) in a fire emergency (Kuligowski et al., 2017).

At present, existing conceptual models scratch only the surface of the development of a larger, comprehensive model of HBiF. These models provide a path forward for the methods that could be used in its eventual development. However, there is much work still to be done to improve our understanding of HBiF, and without this understanding, a comprehensive model is near impossible. For the field to reach its goal and develop a larger understanding of human behaviour in fire, accurate, rigorous, and comprehensive research and theory development must continue. There is still much left to understand, but the ultimate goal of a comprehensive model is in our future.

Independent of the method used to create the conceptual model, it will require a large effort to be validated using different sets of data from emergency events (including fires in different types of structures and with different populations, as well as from analysis of other types of disasters, not limited to building fires) – to ensure that this model is sufficiently generalized to accommodate all types of fire scenarios.

Once a validated conceptual model is developed, extensive work will be required to implement it into current or future evacuation models. Gwynne (Gwynne, 2012) has already begun to consider requirements of the agent-based evacuation modelling tools such that a conceptual model of HBiF could be represented, which was extended in (Kuligowski et al., 2017). The authors first describe a simplified behavioural theory of HBiF, and then outline the model functionality required to represent the theory, including external cues and conditions, cue processing, a roles/social network, spatial map, event map, threat perception, agent attributes, and a response or action generator. They end by providing an example of how the evacuee decision-making process can be represented by an agent-based modelling tool.

After development and implementation, the next question that arises is when and where a conceptual model of HBiF is needed. Evacuation model users would benefit from guidance on its usage for different types of projects and project objectives. It is likely that the development of this conceptual model will be expensive, and therefore, the use of such a model may be expensive as well. There are certain instances (e.g., scenarios, projects, purposes, etc.) where the inclusion of a conceptual behavioural sub-model within an evacuation computer model would be more beneficial than others.

First, there are certain types of fire evacuation scenarios where the use of a conceptual model matters. A conceptual model of HBiF would be most useful in scenarios where most or all of the evacuation timing can be spent in the decision-making process. The domestic setting is a prime example of this phenomenon. In domestic settings, the time to movement from "Point A" to safety (i.e., outside of the residence in the case of a building fire) can be insignificant, especially when compared to the time often spent seeking information, deciding to evacuate, and preparing. Therefore, a conceptual model would be more applicable when modelling evacuation from fires.

With that said, a conceptual model may be beneficial even in scenarios that are dominated by people movement and flow, e.g., stadia evacuations. That is, if the user wishes to explore more than just the evacuation timing of the fire event. Without a conceptual model, the user may superficially treat the evacuation as laminar flow. By doing so, he/she is potentially ignoring the impact of social clusters and group dynamics on evacuation performance. In other words, if a user wishes to study individual experiences of groups/evacuees (at lower levels) during the stadium evacuation, in order to better understand locations of 'turbulent' flow throughout the building or structure, the use of conceptual model is desirable.

Second, there may be certain types of project objectives (over others) that require the use of a conceptual model. In projects where the evacuation model is being used to simulate agents strictly adhering to a specific procedure, the benefits of a conceptual model are limited. An example of this is exploring the results of a procedure whereby the building population evacuates immediately and uses the main exit. This is a legitimate use of current modelling tools, given that the evacuation model used is capable of capturing the outcomes of the agents. In this project, the benefits of a conceptual model are limited because the "behaviour of the occupants" in the modelling scenario can be sufficiently pre-defined by the user. Projects where a conceptual model is of most benefit are those where the user is required to answer "what could happen if…." questions. Essentially, these projects require the model to explore what agents would do, given only a series of initial conditions. In these projects, a model's ability to simulate emergent behaviours and outcomes (i.e., those not completely pre-defined by the user) is crucial, and only possible through the inclusion of a refined and comprehensive conceptual model of HBiF.

At the moment, it is up to the model user to decide, based upon project requirements, the capabilities of the evacuation modelling tool(s) required for the job, and in turn, select the correct/appropriate tool to use. The same would be true when/if a conceptual model was available. Currently, we do not have the capabilities of a conceptual model of HBiF in any of the current evacuation modelling tools. In the future, if these capabilities are made available to model users (either within certain modelling tools or as a sub-model to accompany current tools), users would benefit from a guide that would help them decide when, and for which projects/scenarios, a conceptual model would be beneficial.

5. Applied mathematics: overhead pedestrian tracking for large scale real-life crowd dynamics analyses

Pedestrian monitoring, and in particular the observations of pedestrian trajectories are of key importance for the understanding of pedestrian evacuation behaviour. This contribution discussed a novel technique for pedestrian monitoring as it allows unprecedented, unsupervised, 24/7, months-long, pedestrian measurement campaigns that provided millions of individual trajectories, allowing novel statistical insights. The tracking technique leverages overhead depth-sensors, such as Microsoft Kinects, arranged in grids, and ad hoc pedestrian localization algorithms.

Over time measurement techniques evolved: manual measurements for flux-density relation estimates (e.g. (Seyfried et al., 2007)) has been replaced by increasingly automatized individual(-head) tracking (Boltes and Seyfried, 2013; Zanlungo et al., 2014). Crowd dynamics experiments in real-life conditions are receiving increasing attention, e.g. (Helbing et al., 2007; Zanlungo et al., 2014) as they come as alternatives of laboratory-based, "in vitro", pedestrian data acquisition campaigns, in which experimenters involve groups of voluntaries, that possibly wearing special clothing to aid tracking, take part to crowd flows scenarios. Real-life measurements present two main advantages over laboratory approach: first, they involve pedestrians unaware of being part of a scientific experiment. While in laboratory the measured dynamics is orchestrated, thus unavoidably more or less biased by the experimenter instructions, in real-life pedestrian flows respond to the free will of the randomly involved individuals, allowing to truly expose the stochasticity of pedestrian motion. Secondly, real-life pedestrian measurement campaigns can span over potentially limitless time intervals; therefore, they allow collection of thousands or millions of trajectories. Such a large amount of unbiased data, impossible to collect in a laboratory framework, enables to measure the motion beyond its average quantities and estimate its fluctuations and its characteristic rare events.

Real-life measurements, when targeting the acquisition of thousands of trajectories, must occur in an unsupervised manner, demanding a strong technological effort for robustness and accuracy. For instance, unaware participants can wear any sort of clothing or headgear, that the tracking algorithmic must be able to deal with. Also, in laboratory, the experimenter can fully define "control parameters" for their experiment (e.g. number of individuals involved, crowd density, directionality), while in real-life they are subjected to the randomness of the crowd flow (Corbetta et al., 2017a). In real-life conditions, privacy of the involved crowd is also a crucial issue, as individuals must consent to participate to experiments, especially if not anonymous (e.g. in case tracked individuals remain recognizable in the recorded data).

A novel pedestrian tracking approach was discussed and exemplified with data collection campaigns held respectively in a building of Eindhoven University of Technology (years 2013-2014, about 200.000 trajectories collected, see e.g. (Corbetta et al., 2014) and at Eindhoven train station (years 2014-2015, about 5 millions trajectories collected, see (Corbetta et al., 2017b), cf. Figure 1), analysed the pedestrian dynamics with high statistic resolution, targeting motion fluctuations and rare events.

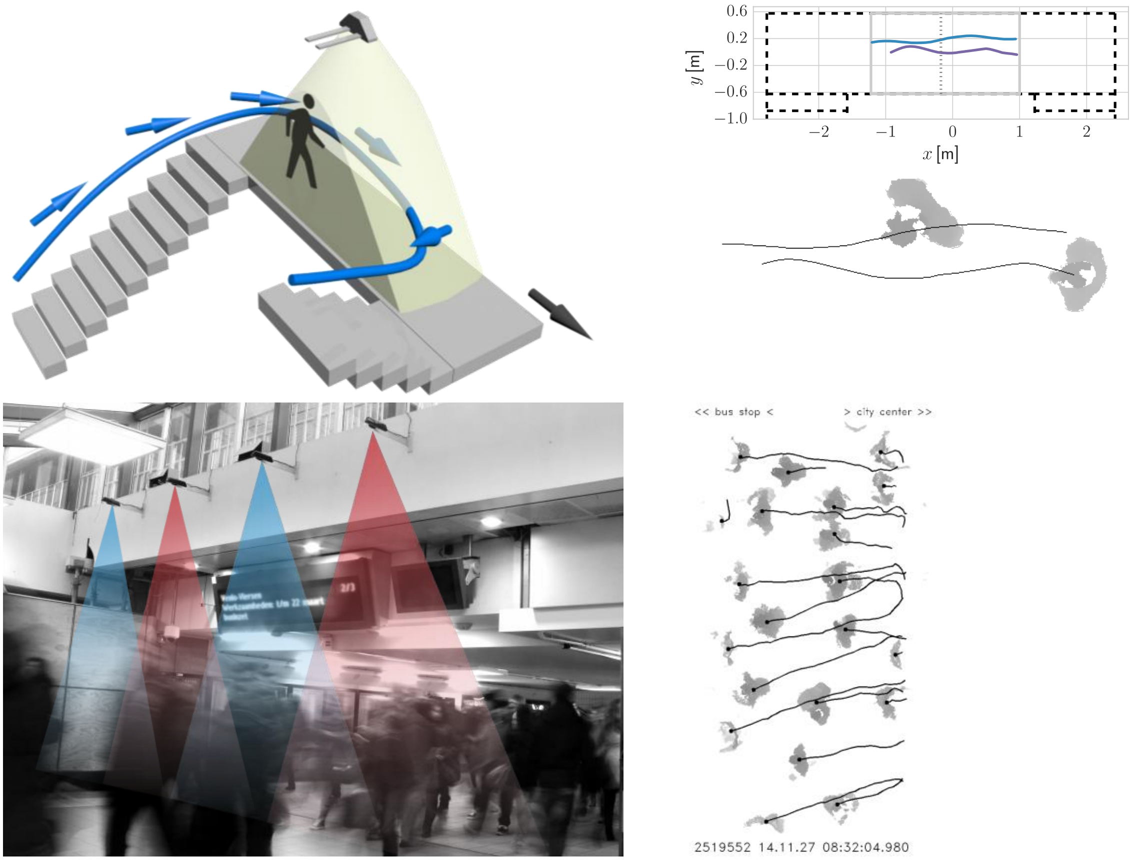

Figure 1. (top) Crowd tracking experiment at the Metaforum Building, Eindhoven University of Technology; setup sketch, example of collected trajectories and related depth maps (figure from (Corbetta et al., 2017b). (bottom) Crowd tracking experiment at Eindhoven train station with four Kinect sensors: snapshot and sample depth map with trajectories. In both cases depth maps have grayscale colorization (figure from (Corbetta et al., 2016)).

5.1. Measurements via overhead depth sensors

The grounds of the measurement technique employed have been firstly and independently posed in (Bršcic et al., 2013; Seer et al., 2014), and leverage depth field signals, acquired via depth sensors, for pedestrian localization. Thanks to the usage of depth map signals pedestrians remain unrecognizable, thus fully preserving the individual privacy.

Depth sensors return distance-field maps, or depth maps. While an ordinary digital image reports pixel-by-pixel a color information (RGB, i.e. three channels), a digital depth map reports the distance between each pixel and the camera plane. This is a single channel (scalar) information, usually encoded in grayscale images. A fairly extended selection of depth sensors is currently available on the market differing in resolution, depth reach, acquisition frequencies and prices (Bršcic et al., 2013; Stoyanov et al., 2011). Since the early 2010s, depth sensors entered the consumer market with devices as Microsoft Kinect, which along with a standard colour camera, is equipped with an infrared structured-light sensor (Stoyanov et al., 2011) and, via an embedded system, it delivers an estimate of the depth map of the scene at VGA resolution (640x480 px) and at 30Hz refresh rate. Microsoft Kinect sensors provide the raw depth images of pedestrians at the basis of the tracking technique considered in this paper.

In the campaigns discussed in (Corbetta et al., 2016, 2017b) either one or four sensors were employed roughly at 4 meters above the ground. The effective spatial coverage provided by a single sensor is about 2m x 2.2m, i.e. within this area heads of subjects up to 1.8m tall are observable without cuts. Sensors are juxosed in a way that a continuous coverage of such effective area is provided. Throughout real-life experimental campaigns, it is possible to collect hundreds of thousands of pedestrian trajectories aiming at unveiling statistic signatures of the pedestrian motion. While individual paths of people may be less relevant to evacuation modelling for fire safety engineering applications, a statistical analysis of the movement and behaviour of a population would be useful to design evacuation safety. The analysis of real-life measurements comes with an intrinsic complexity, determined by the randomness with which different crowding conditions follow one another. In a train station, a diluted flow composed of one or few people can, in a matter of seconds, turn into a dense crowd, e.g. after the arrival of a commuter train. In this sense, data acquired in real-life campaigns come from a (random) sequence of experiments and should undergo an aggregation phase preliminary to the analyses (see Figure 2).

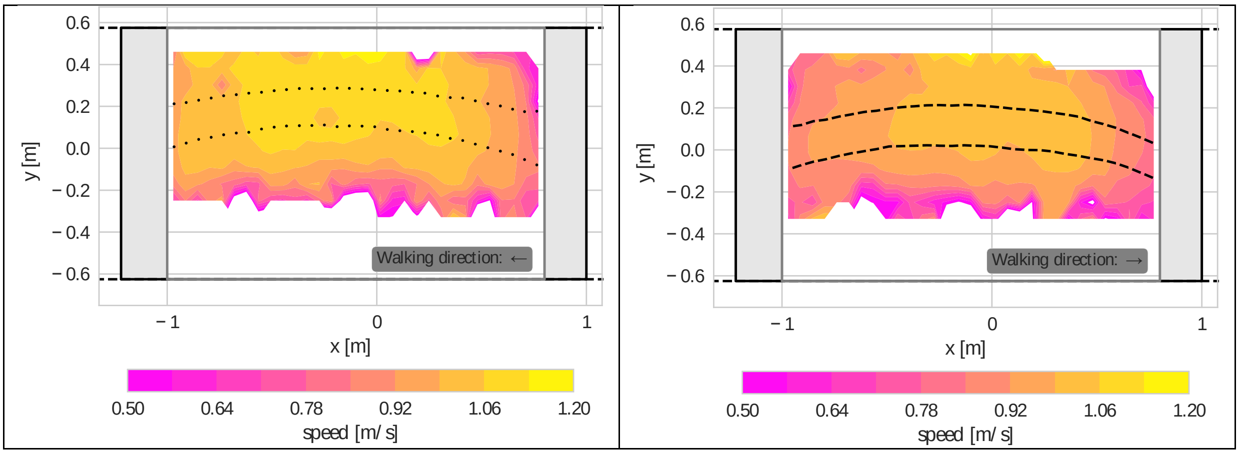

Figure 2. Walking speed distribution and band of preferred positions for pedestrians walking in the landing in Figure 1(top), respectively to the left (left panel, descending direction) and to the right (right panel, ascending direction). Figure from (Corbetta et al., 2016).

A pedestrian tracking algorithm based on overhead depth imaging data enables real-life data collection of pedestrian trajectories with high accuracy. In this context, high statistics measurements enable unprecedented insights in usage patterns. These are relevant toward the comprehension and the quantitative modelling of the complex motion of crowds. Finally, the localization algorithm exploits simple geometric concepts identifying pedestrians as cluster within the foreground of an overhead depth cloud. The geometric simplicity of this algorithm is the key for its execution speed and the high localization accuracy in moderately dense conditions (up to 1.5people/m^2). The algorithm performance, in fact, decreases as soon as the correspondence between point clusters and pedestrian vanishes. This occurs at high densities or in presence of foreground elements which are not pedestrians (strollers, bikes, removable obstacles and so on), that are unavoidably marked as walking individuals. To address such richer scenarios, more complex localization algorithms are necessary, which effectively analyse the frames and classify each element for type. Only for the element classified as pedestrians they further estimate the locations. Recent advancements in machine intelligence and, in particular, in deep learning (LeCun et al., 2015), showed impressive performance at such recognition and localization tasks, making excellent candidates for algorithmic improvements.

6. Transportation: evacuation modelling in the field of transport

In this section, we consider evacuation beyond the confines of a physical structure such as a building or vehicle or otherwise more confined area, and expand the discussion to consider the case of large-scale urban or regional evacuation, for example as a result of a natural disaster such as a wildfire (Veeraswamy et al 2018), a tsunami (Urata and Pel, 2018). As a result, it is also necessary to look beyond the level of individual pedestrians and crowds, and consider how people make various travel decisions and how these collectively result in traffic flows, possibly across multiple modes of transport (e.g. car, public transit, active modes).Thus, evacuation modelling in the field of transport pertains to developing models that: (1) can predict the spatial-temporal traffic conditions in case of an evacuation, (2) conditional on situational factors such as disaster dynamics and human response behaviour, and (3) conditional on strategic factors such as the dissemination of evacuation information and instructions and the deployment of traffic control measures. Such transport models are then used, for example, to assess the evacuation capability of a region, to assess the strengths and weaknesses of an evacuation strategy, or to adopt a model-predictive framework in order to design optimal evacuation strategies. Furthermore, models can be used for theory testing; by developing a model based on a (behavioural) theory, the theory can be tested by verifying the model predictions against empirical data.

A transport modelling framework generally consists of five sub-models (Barceló, 2010; Bayram, 2016; Intini et al., 2018; Murray-Tuite and Wolshon, 2013), where the first four sub-models describe the travel choice behaviour and the fifth sub-model describes the (resulting) traffic flows in the transport network. The travel choice behaviour sub-models have as purpose to predict the decisions that people make both prior to departure and during their trip, and what the collective of these individual decisions yields in terms of travel patterns. These sub-models thus relate to,

1. Trip generation: how many people will evacuate and at what time they will do so,
2. Trip distribution: where they will evacuate to,
3. Modal split: by what mode they will evacuate (e.g. car, public transit, active modes),
4. Traffic assignment: by what route they will evacuate.

However, in changing scales from building to community, it is important to understand that additional factors can influence household decision-making processes and subsequent evacuation behaviour in community-wide disasters. Community-wide evacuation is often complicated by existing household vulnerabilities, e.g., financial constraints, access to a vehicle, age, disabilities, etc. (Cutter et al., 2003; Lindell and Perry, 2012; Wong et al., 2018) and/or potentially aided by existing social ties and relationships within the community (also known as social capital) (Aldrich and Meyer, 2015).

6.1. Existing modelling approaches

Trip generation models (Pel et al., 2012; Wilmot and Mei, 2004) predict the number of people who will evacuate and when these people will depart. Note that contrary to a building evacuation where the evacuation compliance rate is typically close to 100 percent, in a larger-scale evacuation of a region aspects of compliance (i.e. of those under risk, how many will evacuate) and shadow evacuation (i.e. of those not currently directly under threat, how many will still evacuate) are important considerations. Two approaches can be distinguished: two-step static models, and integrated recursive models. In two-step static models, two separate models are estimated: the first model describes the evacuation participation (either the probability for an individual, or the percentage for a population), while the second model describes the evacuation departure time (either as most likely time window for an individual, or as response rate for a population). Then combining the models predictions yields the number of evacuees departing at any specific time. These models are static in the sense that the trip generation is predicted prior to simulating the evacuation, and hence any time-varying changes in the conditions that may influence the trip generation is not accounted for. Typically simplistic statistical distributions are used here, as opposed to explanatory econometric models. This two-step model is commonly applied, likely due to the mathematical simplicity of the approach and the fact that relatively little situation-specific data is required. A main drawback of this two-step static modelling approach is the lack of a behavioural theory underlining the model. In integrated recursive models, integrating the evacuation participation and timing decisions relaxes many of these limitations. This is done by recursively (i.e. interleaving with the evacuation simulation model) predicting the evacuation departures for that specific time. Here typically an econometric model is repeatedly used, which predicts the share of people who decide to evacuate and depart presently, or postpone the decision to evacuate. The econometric model models this binary decision based on the differential utility associated with evacuating (compared to not evacuating) as a function of the current or expected conditions. As these conditions change over time, so can the evacuation decision be predicted dynamically as the incident evolves.

Trip distribution models (Murray-Tuite and Wolshon, 2013; Pel et al., 2012) predict individuals' destination choice. This sub-model is only included in case of an evacuation with some minimal notice time, such that evacuees are actually capable of consciously deciding on their evacuation destination. In case of an evacuation with little to no notice a common modelling assumption is that the evacuation destination is not actively chosen, but instead a mere result of the chosen (presumably most familiar or fastest) evacuation route. That is, evacuees will choose the route that leads them out of the threatened region as soon as possible, and once safe may continue their trip to their final destination. Trip distribution models are almost without an exception always an econometric discrete choice model comprising of two components. The first component estimates the type of location that an individual evacuates to, thereby distinguishing: family and friends, public accommodation (e.g. hotels), and dedicated evacuation shelter. The second component estimates the specific destination, conditional to the type of location. The destination decision depends on characteristics of the available alternatives (e.g. costs, capacity, perceived safety) and the travel resistance to reach the destination (e.g. travel distance, travel time).

Modal split models (Intini et al., 2018) predict the mode of transport that evacuees will use. Transport modelling tends to focus on evacuating suburbs and regions, where evacuation distances require some form of motorised transport. At the same time, many empirical examples (of evacuations due to wildfires, hurricanes, flooding, and storms) have shown that when a car is available, it is the preferred mode of transport for evacuation. This is ascribed to the fact that evacuating by car enables securing the safety of the car as asset while also it enables to bring along other personal items and assets (and makes it easier for a household to evacuate together). Therefore, it is seldom that a modal split model with be estimated. Instead, more commonly, census data and local expert knowledge/judgement is used to estimate the population share who have access to a car and the population share who will rely on public transport and dedicated evacuation (bus) services. The multimodality of public transport travel (i.e. using busses, trams, trains) as well as the interaction with cars on the road can be modelled using a multimodal transport model (Van der Gun et al., 2016).

Traffic assignment models (Barceló, 2010; Intini et al., 2018; Pel et al., 2012) predict the route that evacuees will follow. Although the vast majority of evacuation models do explicitly include a traffic assignment sub-model, there are a number of studies that sidestep this sub-model. One way is to simply insert pre-defined evacuation routes, thus simulating mandatory prescribed routes to test various evacuation route strategies. This however does assume full compliance, which is most certainly too strict an assumption to make. Another way to sidestep this sub-model is to simply estimate the ratio between the total spatially distributed travel demand (i.e. number of travellers) and the capacity bottlenecks in the road network (i.e. number of travellers that can pass per unit of time), which then together with some correction terms give a 'first guess' on the minimum time required for the complete evacuation. Apart from the questionable validity of this approach, more importantly, this method does not provide insight into: the dynamic evacuation traffic conditions, the underlying (success and failure) factors that determine the evacuation process, and the benefits of deploying control measures.

In pre-trip traffic assignment models, evacuees are assumed to choose their route from origin to destination upon departure, and to not switch routes while travelling. Route choice behaviour is predicted using an econometric discrete choice model that is based on the currently prevailing or expected route conditions. The pre-trip route choice paradigm may appear inappropriate to model route decisions under evacuation conditions. This is because the sub-model is adopted from other transport models for long-term planning studies. There the pre-trip route choice model is embedded in an iterative procedure mimicking how travellers build up experiences (from one iteration to the next) leading to well-informed expectations about what traffic conditions to expect, thus iteratively updating their route choice until a steady (equilibrium) state has been reached. In on-trip traffic assignment models, the assumption that evacuees cannot deviate from their (pre-trip) chosen route is relaxed. Here, evacuees observe the prevailing conditions and make route choice decisions accordingly. In hybrid traffic assignment models, both pre-trip and on-trip decisions are modelled. This way, evacuees are assumed to choose an initial route upon departure, after which they may adapt their route during their trip. They might do so when prevailing traffic conditions are such that they are better off (or have the feeling of being better off) by deviating to another route. This type of model is also used to evaluate varying degrees of compliance towards dedicated evacuation routes (Pel et al., 2010).

Traffic flow models (Leutzbach, 2012) predict how vehicles drive through the infrastructure network and interact with other traffic, thereby computing travel times and congestion dynamics. The majority of traffic flow models are dynamic, in the sense that they use simulation to compute the time-varying traffic conditions. Traffic flow models are best categorised along two axes; the first being the aggregation level for traffic representation and propagation; the second being whether flows are based on queueing theory or kinematic wave theory (Hoogendoorn and Bovy, 2001). Traffic flow models can be microscopic, macroscopic, or mesoscopic depending on the combination of traffic representation and propagation. The level of detail in the microscopic models is ideal for studying driving behaviour under evacuation conditions. For sake of computation time and model complexity, macroscopic and mesoscopic models are preferred in evacuation studies for larger regions.

6.2. Model applications and challenges

In evacuation modelling in the field of transport, models are used (1) to assess the evacuation capability of a region, (2) to assess the strengths and weaknesses of an evacuation strategy, or

(3) to adopt a model-predictive framework in order to design optimal evacuation strategies.

The essence of a fast and smooth evacuation lies in the balance between the travel demand (i.e. number of evacuees) and the network capacity (i.e. sustainable exit flow). Hence, likewise models are used to investigate demand and capacity strategies that aim to facilitate the evacuation. Demand-side evacuation strategies include 1) Phased evacuation, 2) Sheltering-in-place or close by, 3) Reducing shadow evacuation and background traffic, 4) Prescribed evacuation routes. Capacity-side evacuation strategies include instead 1) Contraflow, 2) Crossing elimination (i.e., prohibition of certain turning), 3) Special signal timings, 4) Dedicated public transport services, 5) Use of hard shoulders (i.e., emergency lanes). The use of these strategies in the transportation modelling domain can be a useful starting point for comparison with existing and future building evacuation modelling applications.

Next to evaluating the expected effects of evacuation strategies, the sensitivity of these strategies is tested using model sensitivity analyses. Such sensitivity analyses are conducted by a controlled varying of a part of the model (scenario input, model assumptions/sub-models, or model parameters) to test how this leads to changes in model output. Common analyses are to test the impact of 1) Spatial-temporal disaster dynamics, 2) Failure of transport network components, 3) Population characteristics and behaviour, 4) Failure to deploy control measures, 5) Modelling simplifications.

A set of challenges have been identified starting from the modelling capabilities and applications. Model calibration of evacuation transport models remains an issue. Choice models are calibrated using data from stated preference surveys and post-disaster questionnaires, while the traffic flow models are calibrated using data from empirical traffic counts and driving simulator experiments. This amount of empirical data is growing, giving insight into evacuees' activity-travel patterns, the information that they had at hand at the time, and the resulting traffic flows in the region. However, there are very few modelling studies that investigate in what way these calibrated (sub-)models can be applied to other regions, in a different cultural context, and possibly other disaster dynamics.

The second research challenge is to embed evacuation traffic models into decision support tools used in disaster management. Evidently, this requires an interdisciplinary approach with social scientists, structural engineers, transport engineers, and researchers from fields specifically related to the disaster type; possibly also incorporating the fields of humanitarian logistics and disaster relief operations. Besides the practical relevance of disaster management decision support tools, such an interdisciplinary approach can lead to greater holistic understanding of evacuations, and aid in refining our evacuation (transport) models.

The third research challenge is to model how new technologies are utilised. This can pertain to information dissemination via social media, mobile devices and in-vehicle devices, with real-time information on disaster, infrastructure, and traffic conditions. It is currently insufficiently understood how this may affect evacuees' behaviour (across all sub-models) and how this can be incorporated in evacuation transport models. Furthermore, this is also relevant for data collection methods, for example, relying on GSM and GPS traces. How such data can be used real-time in evacuation management strategies, as well as used post-disaster in model development and calibration, is a challenge for future research.

7. Dynamic simulation and biomechanics: An analysis of human biomechanics and motor control during evacuation movement.

Biomechanics and closely related fields can describe key elements of locomotion that are employed in the process of walking in congested space. In order to understand how these fields can interface with the discipline of crowd and evacuation modelling, we should consider the following areas of study:

a. The study of biomechanics evaluates the motion of a living organism and the effect of force on a living organism (Hamill et al., 2015)
b. The study of motor control: an area of natural science exploring how the central nervous system (CNS) produces purposeful, coordinated movements in its interaction with the rest of the body and with the environment.

These fields of study are inextricably linked to the process of evacuation, particularly in terms of how humans move in relation to each other. The collective movement of individuals is encapsulated (in fire and life safety) as crowd flow. The flow metric emerges from aggregating the sum movement of the escaping individuals. However the design guides, research and computer modelling for life and fire safety have largely ignored the key aspects of biomechanics and motor control. An improved understanding of the fundamental biomechanical processes of human motion can be useful to improve predictions of crowd movement. This is particularly important to evaluate the impact of changing demographics, which would include in the future an aging population and an increasingly obese population , thus requiring a deeper understanding of the locomotion mechanisms.

The field of evacuation modelling for fire safety engineering applications should aim at removing “rule of thumb” approximations of crowd flow and lead to much more rigorous assessments of safety based on biomechanics. The latest United Nations report on World Population Ageing (United Nations, 2015), states that between 2015 and 2030, the number of people in the world aged 60 years or over is projected to grow by 56 per cent, from 901 million to 1.4 billion, and by 2050, the global population of older persons is projected to more than double its size in 2015, reaching nearly 2.1 billion. Preparing for the economic and social shifts associated with an ageing population is thus essential. Population demographics have changed over the past 50 years and will change even more, thus originators of the simple flow aggregate values need to be replaced. The effects of ageing on gait velocity, step width, step length and coefficient of friction, horizontal sway and perception of per personal space needs must logically impact on how heterogeneous crowds move in confined spaces, both in an emergency or normal situation. However, we currently have limited understanding on the fundamentals of how - and the extent to which - this does impact crowd flow.

7.1. Biomechanical processes

There are many aspects of locomotion biomechanics that *can* be considered by Fire Safety Engineers, such as, 1) walking, 2) running (while it is accepted that in most fire engineering designs people are assumed to be walking, understanding running mechanisms could provide useful insight into walking behaviours), 3) Assisting others, 4) reacting to stimuli, 5) accelerating, decelerating, turning, 6) passing through openings, 7) adapting gait to confined space, 8) preserving one’s own personal space/respecting others’ personal space, 9) walking with encumbrances/disabilities, 10) transitioning between multiple phases of the above processes.

Many aspects of the above processes have been well studied in the biomechanics and motor control disciplines, particularly in the fields of sport and exercise science, sports medicine, health sciences and public health. How these are measured, analysed, calculated or simulated can be of interest to Fire Safety Engineers. Opportunities for a more integrated approach across disciplines in advancing an important frontier in human movement analysis are explored, i.e. how interactive movement in a complex environment can be measured, understood and modelled.

Gait analysis of walking is usually expressed in terms of spatial parameters e.g. step width, stride length or joint range of motion, and temporal parameters e.g. stride time, swing time, step time. The gait cycle, or gait stride, can be broken down in two broad phases: stance and swing (Perry and Burnfield, 2010). The time dimensions of the walking cycle includes single and double support time, i.e. the time when only leg or two legs are touching the ground, respectively. These are important parameters as the time spent in double support changes with age and disability, giving an indication of the level of stability that is being exploited within a person. Spatial parameters such as stride length and step width also give an indication of the limits of stability in the anterior-posterior direction and lateral body sway.

Another commonly used variable in gait analysis is gait speed. It is a reliable, valid, sensitive and specific measure that correlates with functional ability, and balance confidence and predicts future health status, functional decline, discharge location and mortality (Fritz and Lusardi).

Concerning running, the use of a deterministic model allows the understanding of the basic biomechanics of running. The deterministic model is a modelling paradigm that determines the relationships between a movement outcome measure and the biomechanical factors that produce such a measure (Hay, 1994). First, the model is made up of mechanical quantities or appropriate combinations of mechanical quantities. Secondly, all the factors included at one level of the model must completely determine the factors included at the next highest level, hence the term deterministic. This is a potential approach that could be used to investigate the important factors that determine movement in a crowd. The first level would start with “gait speed in a crowd”, and the next level may include stride time/stride frequency and stride length.

The key elements of walking in congested space include (see Figure 3).

1. Gait - particularly step & stride length
2. Cadence - the frequency of a completed step cycle
3. Avoiding collision - factors include response time and anticipating the movement of others
4. ‘Comfort’ space where, in addition to space for leg-swing and avoiding a collision, we allow a buffer of space where we are comfortably allowing enough time and distance to avoid unexpected inter-person contact.

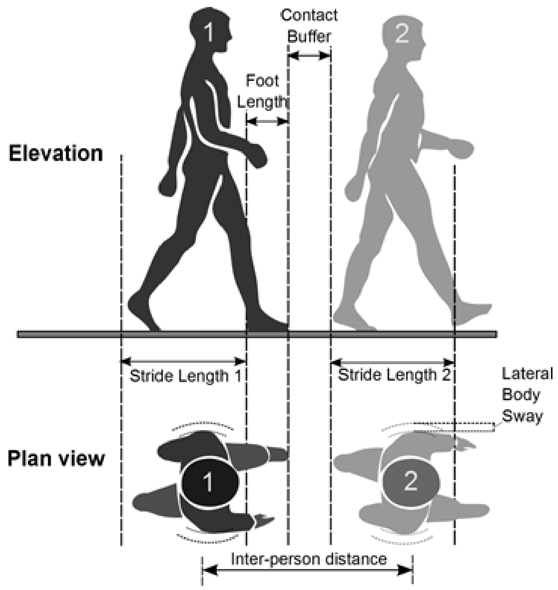

Figure 3. Elements of stride/distance in congested space

Figure 3. (a) Relationship between velocity and inter-person distance (Thompson et al., 2015).

Early assessments of individual movements in congested space (Thompson and Marchant, 1995) have involved the assessment of inter-person distance and walking speed. In addition to the relationship between distance and speed, these early studies used the general approximation of acceleration and deceleration as 10% of unimpeded walking speed over 0.1 seconds, and also 10 degrees for rotational body ‘twist’ limitation over the same time period. When these parameters were implemented in the computer model Simulex (Thompson and Marchant, 1995) then it reproduced flow rates of 1.34 people/m/s for a nominal ‘commuter’ population type, using databases available at the time (Fruin, 1987; Predtechenskii and Milinskii, 1978).

Many commonly encountered computer models use aggregated relationships for the speed and flow curves (Fruin, 1987; Predtechenskii and Milinskii, 1978). Similar correlations for movement on staircases (Burghardt et al., 2013). However, these curves take no account of population demographic differences, i.e., no account is taken of physical anthropology of the people.

In contrast, the biomechanics and motor control literature abounds with movement data that has been recorded using an array of technologies. The field of movement analysis originated with the advent of moving pictures, resulting in playback facilities that enabled the analysis of the quality of the movement. The vast majority of quantitative analysis of kinematic data has been carried out on individual research subjects (Kontaxis et al., 2009). Development of techniques specifically for the accurate, high resolution analysis of movement of people in crowds is a frontier in the field of movement analysis that will very much impact a number of fields of study e.g. psychology, ageing, security and crowd flow in evacuation.

The next step in the interdisciplinary research field of crowd biomechanics is to develop a fundamental understanding of movement of mixed populations. Potential biomechanical parameters that may influence individual movement and interaction in populated spaces needs to be assessed in a deterministic approach similar to Hay's models (Hay, 1994). Finally, there is need to explore how physiological, social, psychological and environmental factors influence the identified fundamental biomechanical parameters, across a range of populations.

8. Discussion: Quo vadis evacuation modelling?

The presentations of the panellists generated several discussions concerning future possible directions for evacuation modelling with the discussion focusing on two key issues, should tuning parameters of existing sub-models or incorporating new features be prioritized. A general discussion with the whole workshop audience also took place after all panellists' presentations were given. During the presentations and the discussion, two rapporteurs wrote down the main issues discussed during the workshop. The first topic of discussion concerned the challenges of using data-sets derived from different methodologies, as a set of different methods were proposed by various panellists. The workshop panellists agreed that the assessment of what can be considered representative data-sets remain for any type of research methods. The trade-offs between different methods (e.g., ecological validity vs. experimental control) should be assessed case-by-case rather than analysing the validity issue of a single method. There was agreement on avoiding the direct use of virtual reality data for modelling purposes without a careful evaluation of their validity because at least to date, it cannot be used to extract absolute parameter values of, for example, walking speed. The specific strength of the experimental approach in VR over uncontrolled observations is the possibility to test specific hypotheses and draw causal inferences on human behaviour (Kinateder et al., 2014c). Similar trade-offs might be observed while using behavioural intention questionnaires to assist model development. Limitations have to be identified for all type of research methods and data need to be interpreted for the context of application.

The presentation concerning psychology/human factors led to an interesting discussion concerning the applicability of data obtained from controlled psychophysical experiments in the fire safety engineering context. For example, while in most evacuation scenarios occupants would not be directly exposed to approaching smoke, psychophysical experiments provide basic research insights that can be used to evaluate not only approaching smoke but also smoke changing its density, thus making it useful to evaluate behaviour of people immersed in smoke.

Another important point discussed related to the exact meaning of validation in the context of evacuation modelling, as this was a point raised in several presentations. Questions were made if the concept should relate to the outcome of an evacuation (e.g., the precision at which RSET can be predicted) or how accurately a model describes evacuation behaviour itself. The need for the definition of an overarching concept of behaviour was identified along with the need for a common set of references for validation of each component of behaviours. Although a comprehensive validated conceptual model would increase the credibility of the field and the use of models, it is important to identify solutions given the current state of the art in which such a comprehensive model does not exist. The discussion mostly focused on agent-based modelling, as this is likely the most feasible solution to perform such enhancements. Alternative (generally simpler) approaches are also used nowadays to represent evacuation (e.g. hydraulic models (Gwynne and Rosenbaum, 2016), cellular automata (Pelechano and Malkawi, 2008)), but they were not the main focus of the discussion as they present several limitations in terms of their ability to represent complex behaviours. In this context, recent efforts have been focussing on providing guidance on development and use of evacuation models given the existing state of research (Gwynne et al., 2015;

Kuligowski et al., 2017). The conclusion for this particular cross-roads, was that future research should therefore focus on both possible pathways, 1) the development a comprehensive human behaviour in fire model, as well as 2) enhance current models.

Another solution to the current lack of a comprehensive validated conceptual model is the collection and use of big pedestrian movement data as the basis for development and evaluation of evacuation models. Novel methodologies for automated tracking of hundreds of thousands of trajectories (Corbetta et al., 2016) were discussed as they open up for a completely new approach for development and validation of models which relies on high level statistics rather than fundamental properties of each individual. Key issues would be in this case the clustering of homogenous data. An important challenge is the need for pedestrian monitoring techniques able to allow understanding of the characteristics of the population observed at a microscopic level for the extrapolation of findings to new scenarios.

The big data approach is somehow complementary with the approach discussed in the presentation on biomechanics and dynamics simulation as the suggestion was here instead to look at the fundamental biomechanics variables of human motion. The main advantage is the possibility of the latter approach is to extend prediction to aging populations. The main drawback is the sheer size and number of the data-sets that need to be collected. This issue led to a discussion on the assessment of the validity of some of the data-sets implemented in evacuation models, which are in some instances collected decades ago (Fruin, 1987; Predtechenskii and Milinskii, 1978). For instance, in case of significant levels of congestions, average speeds may be comparable between those data-sets and more recent data (Galea et al., 2012).

The level at which it is necessary to study crowd evacuation dynamics was also discussed in light of current research performed in the traffic modelling domain. In fact, similar issues take place in the transport field on the preferable modelling approach (macroscopic, microscopic, mesoscopic). This discussion led to the consideration that the assessment of the phenomenon of interest and subsequent model application is the first step for identifying the most appropriate modelling approach to use. Following this, the trade-off between computational time and complexity should be the considered for the definition of the appropriate method of analysis. In this context, the use of hybrid models can be a good solution to adopt the most suitable approach for different conditions (i.e. by modifying the modelling scale within the same model in relation to the variables of interest) (Chooramun et al, 2012, Chooramun et al., 2017).

It should be acknowledged that each panellists' research work concerned the topic area they presented, thus potential biases can be present. The final discussion focussed on the next steps needed for the definition of a common framework for components that evacuation modellers and developers should consider. The point of view of regulators was here considered, as the first important step was identified in the need for bridging existing literature and research with day-to-day use. Following this issue, an important challenge to consider is that the evacuation design is often done once in the life of a building. This means the designers have to take into consideration the potential uses of the buildings and people demographics in the future. For this reason, future models and research efforts in the field should start from the premise of assessing the applicability of their models to a population which does is not necessarily in line with current today building population.

The key needed actions to develop and implement a roadmap for the evacuation modelling field in the fire engineering domain are listed below:

1) Identification of lessons learnt from the model developments in other fields, i.e. what can we learn from other fields? What data can we use? What modelling approaches can be adopted?
2) Identification of the key data gaps concerning pedestrian movement and behaviour, i.e. what we know we do not know and how should we collect this data?
3) Identification of the key modelling gaps, i.e., what conceptual models and sub-models need to be developed/improved?
4) Development of a robust and internationally recognized verification and validation standard testing procedure for evacuation models used in fire safety engineering.

9. Conclusion

The workshop *New approaches to evacuation modelling* within the IAFSS Symposium has been a great opportunity to gather experts outside of the field of fire safety engineering and evacuation modelling experts. The benefits of exchanging information between these two groups appeared evident during the workshop given the successful exchange of ideas. Suggestions towards developments and improvements of evacuation models based on a multi-disciplinary premise were given, analysing the advantages and drawbacks of different approaches and providing suggestions for future research in this field.

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